BINUS UNIVERSITY GRADUATE PROGRAM

People Innovation Excellence

IDENTIFYING DROWSY DRIVER BY USING HEART RATE DETECTION WITH DEEP LEARNING

Background

Road accidents are one of the most critical priorities for managing road traffic around the world. This leads several automobile associations, research institute and manufacturers to invent and implement safety systems to prevent the drivers sleepy.

One of safety systems has been reached is using heart rate data to detect drowsiness level.

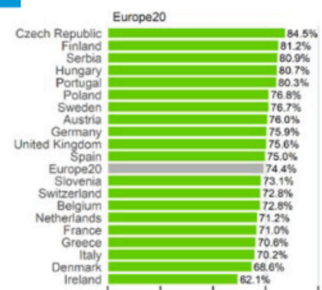


Figure Drowsiness as A Factor of Road Accident

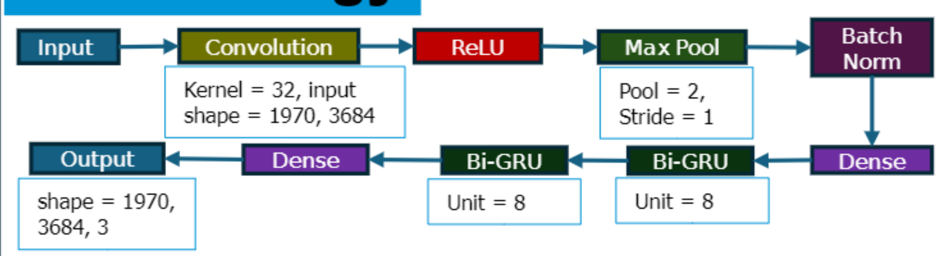
Electrocardiography (ECG) is one the most common methods to measure the heart rate of patients and gives the most accurate result to be obtained in some research. That data will be training and testing source to be modelled on well-know combined forward and back propagation deep learning, which is CNN-GRU.

Previous Works

Isuru et al (2019) used CNN-GRU to classify the level of sleepiness of healthy subjects and clinical patient subjects. The subjects were taken pulse activity from electroencephalography (EEG) and electrooculography (EOG) devices, which achieved an overall accuracy of 89.3% with a f1-score of 0.89 for healthy subjects, and 0.92 for clinical patient subjects.

Clemens Brunner and Florian Hofer (2023) created SleepECG with GRU-based model to classify drowsiness, with achievement 83% of accuracy to classify wake-sleep state for every patient.

Methodology



Result and Discussion

CNN-GRU vs CNN vs Bi-GRU

Classifier	Model	Tipe Proses	Acc (%)	Cohen's Kappa	Precision (%)		F1 score (%)	
					Sleep	Wake	Sleep	Wake
Wake-REM	GRU	CPU	79,84	0,5459	88	65	85	77
	CNN-GRU		83,06	0,6013	88	73	88	72
	CNN		73,34	0,4262	86	55	84	70
	GRU	A100	80,42	0,5416	88	65	87	72
	CNN-GRU		82,88	0,6014	88	72	88	73
	CNN		80,64	0,5059	82	77	87	63
	GRU	Edge Computing	76,20	0,4749	87	59	82	75
	CNN-GRU		81,78	0,594	87	74	88	71
	CNN		72,21	0,4187	86	50	83	71

The accuracy and Kappa values of CNN-GRU with edge computing are competitive if compared with CPU and A100. Those reached 81,78% and 0.594. Meanwhile, the accuracy and Cohen's Kappa values of GRU reached 76.20% and 0.4749. These results are very different when the data is trained using MESA. Although, it has some work to improve F1-score for percentage of "Wake" stage, which only reach 71% compared to CNN (71%) and GRU (75%).

CNN-GRU vs Others

Classifier	Model	Acc (%)	Cohen's Kappa	F1 score (%)		Artikel
				Sleep	Wake	
Wake - Sleep	CNN	83,1	0,41	58,2		Malik et al
Wake - Sleep	GRU	79,84	0,5459	85	77	Brunner dan Hafor
Wake-N1-N2-N3-Sleep	MixSleepNet (CGN & 3D-CNN Modules)	81,3	0,757	90,8	81,3	Ji et al
Wake - Sleep	CNN-GRU (Cloud Comp)	83,06	0,6013	88	72	Proposed model
	CNN-GRU (Edge Computing)	74,08	0.4394	80	63	

The proposed model has exceeded the previous Kappa coefficient and F1 score comparing to CNN model from Malik et al (2018) and GRU from Brunner and Hafor (2023). However, the result from Google Colab has slight lower value for accuracy from both model. It will be an opposite if MixSleepNet from Ji et al (2024) is compared. The Kappa and F1-score are better than the proposed model, which are 0.757, 90.8% for sleep score, and 81.3% for wake score. This happened due to the structure of the model has developed graphic learning layer and pseudo 3D convolution layer three times. Meanwhile, CNN-GRU is just simple one-dimensional convolutional layer with bi-directional GRU.

Conclusion

Drowsiness is a problem that must be overcome to improve safety when driving a vehicle. To overcome this problem, a driving monitoring system is a solution applied in driving a vehicle. One of the monitoring systems used is to rely on ECG data from the driver to detect drowsiness. To optimize data from the ECG, the data is extracted into HRV (heart rate variability) data and modeled in the form of a deep learning model. One of the deep learning models used is CNN-GRU. This model provides higher accuracy and Kappa coefficient (82.88%; 0.6014) compared to the GRU model (79.32%, 0.5461) designed by Brunner and Hafor (2023). In addition, CNN-GRU also has a design that can reduce RAM usage from 8.1 GB to 7.4 GB and power usage on the GPU from 62.21 Watts to 45.41 Watts. Thus, the CNN-GRU model can provide RAM and power efficiency with better accuracy and Kappa coefficient compared to the GRU model.

Although it has the potential to increase accuracy and Cohen's Kappa values, CNN-GRU needs to be further developed to have higher Kappa, precision, and F1 Score values compared to several models that can classify 5 levels of sleepiness, such as MixSleepNet, CoSleepNet, and LSTM-Ladder Network. CNN-GRU development can be done by using:

1. Larger datasets for training and testing, such as SleepEDF, ISRUC-Sleep, DRM-SUB, and other accessible datasets,
2. Larger stride and padding structures with padding values that are not limited to zero padding,
3. Improved filter values on CNN and adjusted to the dimensions of the dataset entered before processing and have more compact/smaller dimensions, and
4. Using two-dimensional/more scales to process data with deep learning models.

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